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An Uncertainty-aware Workflow for Keyhole Surgery Planning using Hierarchical Image Semantics

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ABSTRACT

Keyhole surgeries become increasingly important in clinical daily routine as they help minimizing the damage of a patient's healthy tissue. The planning of keyhole surgeries is based on medical imaging and an important factor that influences the surgeries' success. Due to the image reconstruction process, medical image data contains uncertainty that exacerbates the planning of a keyhole surgery. In this paper we present a visual workflow that helps clinicians to examine and compare different surgery paths as well as visualizing the patients' affected tissue. The analysis is based on the concept of hierarchical image semantics, that segment the underlying image data with respect to the input images' uncertainty and the users understanding of tissue composition. Users can define arbitrary surgery paths that they need to investigate further. The defined paths can be queried by a rating function to identify paths that fulfill user-defined properties. The workflow allows a visual inspection of the affected tissues and its substructures. Therefore, the workflow includes a linked view system indicating the three-dimensional location of selected surgery paths as well as how these paths affect the patients tissue. To show the effectiveness of the presented approach, we applied it to the planning of a keyhole surgery of a brain tumor removal and a kneecap surgery.

1. Introduction

Keyhole surgeries become increasingly important in clinical daily routine, as they help keeping the impact to patient's healthy tissue minimal. To accomplish such a type of surgery, medical doctors need to determine a proper surgery corridor that allows them to reach the location where the actual surgery takes place. Determining this corridor is based on medical image data that is captured of the patient. While planning a keyhole surgery, medical doctors need to identify areas, that should not be affected by the surgery and discuss possible risks during the surgery itself Reisch et al. (2013).

Planning keyhole surgeries can be difficult, as the underlying image data is affected by uncertainty resulting from the image reconstruction process. Including this type of information into the planning process of a keyhole surgery is not trivial, as available visualization techniques are not communicating this type of information. Furthermore, the state of the art in reviewing medical image data in clinical daily routine does not provide a suitable visualization methodology that helps decision makers discuss surgery options intuitively and fast (see Section 2).

To solve this problem, this paper presents a novel visual analytics workflow to plan keyhole surgeries based on hierarchical image semantics (see Section 4). The workflow carefully selects suitable visualization and analysis methods and combines them to allow an easy to understand workflow for surgery analysis. Based on an extensive analysis of the keyhole surgery task (see Section 3), our workflow consists of four major steps, that are designed to be proceeded by medical doctors intuitively: In Step 1, medical doctors can define a hierarchical image semantic that outputs a segmentation containing semantic seg-

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ments that are presented in a probabilistic manner according to the uncertainty of the underlying image data. In a second step, users can define different possible surgery corridors, that need to be examined and compared. After that, medical doctors can query the defined paths expressing structures in the human body that should not be affected. Finally, we provide an intuitive visualization consisting of a linked view. The first view shows a three-dimensional rendering of the most important human structures, the patients body and all surgery corridors that are queried. In the second view, all queried paths are presented in a two-dimensional visualization indicating all tissues, that are affected as well as highlighting areas that cannot be determined clearly as the underlying image data is affected by uncertainty. This forms a visual feedback loop that helps medical doctors adjusting their surgery paths and determining the risks of a chosen surgery corridor.

Therefore, this paper contributes:

- An requirements analysis of a proper workflow for keyhole surgery planning
- An visual analytics workflow including uncertainty information, that allows medical users to plan keyhole surgeries
- An intuitive visualization of keyhole surgery corridors that communicates the uncertainty of the underlying image data

To show the effectiveness of the presented technique, we applied the visual analytics workflow to plan two different keyhole surgery scenarios. First, we plan the removing of a brain tumor and second we apply our technique to the surgery of a kneecap in Section 5. We discuss the presented approach and its results in Section 6. At last, Section 7 will conclude this work and point out future directions.

2. Related Work

The following section will discuss the state of the art in surgery analysis visualization as well as uncertainty visualizations in the medical area with respect to surgery planning scenarios.

2.1. Visual Analysis in Surgery Planning

Visualizations are a key concept in assisting medical doctors during the planning of surgeries Robb (1999). It helps clinicians understand their data and make decisions for further treatment and surgeries. The following Section summarizes visualization techniques that help medical doctors to plan surgeries.

Buchart et. al. Buchart et al. (2009) presented a visualization that helps medical doctors understanding the spatial context of the captured image data to improve the planning of a surgery. Although this is an important aspect of a surgery planning, the approach does not allow to visualize and estimate the quality of a surgery path. Therefore, the presented approach includes an intuitive visualization of surgery paths and the tissues, that are affected.

Gering et al. Gering et al. (1999) presented a methodology, that includes surgery path geometries in the slice-by-slice reviewing methodology used in clinical daily routine. Although, this technique is build on the most prominent reviewing method in clinical daily routine, it can be hard to follow surgery paths throughout the patients body while solely reviewing a single slice at a time. Therefore, the presented visualization aims to combine the spatial aspect of the surgery corridor geometry with the easy to use 2D representation.

A variety of approaches visualizes human organs or structures and their location with respect to the surgery corridor by using isosurfaces Steen and Widegren (2013); Georgii et al. (2016). Although this is a good starting point for the presented work, a visualization solely based on isosurfaces can either result in visual clutter or structures need to be discarded in the visualization. To solve this problem, the presented approach introduces a visualization type, that is capable of visualizing all structures in the human body that are affected by a surgery path.

Several approaches aim to improve the visualization of a patients tissue to allow medical doctors to asses the quality of an option for a surgery setting Paolis et al. (2010); Mhler and Preim (2010). Although this can give medical doctors a good impression of risky areas during an operation, the visualizations do not include a mechanism to plan and test surgery corridors or the manner they interfere with the patients tissue. Therefore, the presented visualization allows medical doctors to specifically plan surgery corridors and review their effect on the patients tissue.

Smit et al. Smit et al. (2017) presented a visualization technique based on iso-surfaces, that aims to visualize the target structures of the surgery and risky areas surrounding them . Although this gives users an first impression of the shape and size of the target structure, the visualization does not form a workflow where users can plan the required surgery. Therefore, the presented paper allows users to determine possible surgery paths and visualize the structures of the human body that affect them.

Girod et al Girod et al. (1995) presented a method, that is able to improve the visual representation of human soft tissues, as they are usually hard to identify in medical image data. Therefore, they utilize a segmentation, that does not include uncertainty information Furthermore, the underlying segmentation does not provide uncertainty information. Uncertainty is an important factor in medicine, as medical image data is affected by uncertainty. Therefore, the presented workflow quantifies and communicates uncertainty throughout the entire surgery planning process.

2.2. Uncertainty Visualization of Medical Image Data

In the medical field, uncertainty visualization become increasingly important as they can help medical doctors refine their diagnosis or plan proper treatments. As the underlying image data is affected by uncertainty due to the reconstruction process, the quantification and communication of image uncertainty for medical tasks is crucial. An overview of uncertainty visualization is given in Bonneau et al. (2014). The following section will discuss the most relevant work considering the planning of keyhole surgeries.

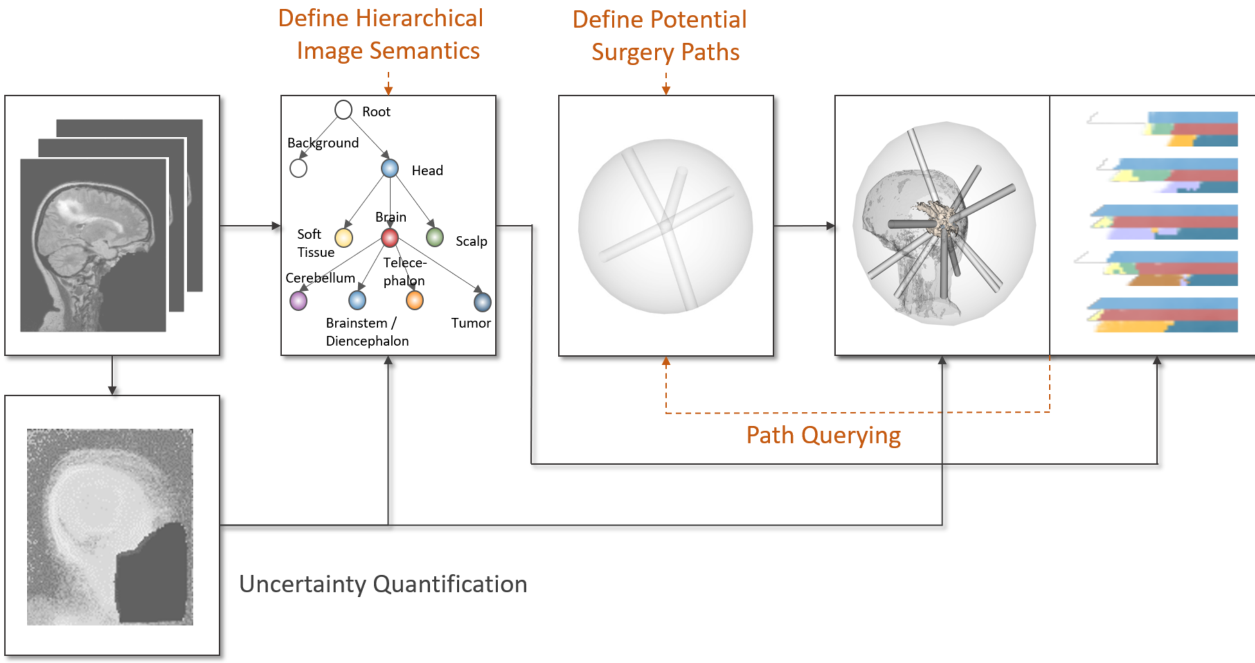

Fig. 1. Overview of the visual anaytics workflow to plan keyhole surgeries. The uncertainty of the input image is quantified and propagated throughout the planning process. The planning process consists of four major steps: 1) Users can create an hierarchical image semantic. 2) Potential surgery corridors can be defined. 3) Users can query the defined surgery corridors by setting restricted or desirable areas. 4) Visual feedback loop to improve the parameters of a proper surgery corridor.

Simpson et al. Simpson et al. (2006) performed a study that showed how uncertainty information can enhance the planning of surgery. Motivated by these results, the presented workflow utilizes uncertainty information of the input image to assist users while identifying risks during the planning of a surgery.

Lundström et al. Lundström et al. (2007) presented an uncertainty-aware visualization for volume rendering tasks in medical applications. Therefore, they adapt transfer function for volume rendering thus it is able to express the uncertainty of the underlying image data. Although this gives medical doctors an insight to the underlying image data, the approach is not sufficient to plan surgeries as it does not allow to examine surgery paths. In contrast to this approach, the presented workflow utilizes uncertainty information to guide user through the entire planning of a keyhole surgery.

Medical image representations including uncertainty information can be found for ultrasonic data Berge et al. (2015) as well as medical image segmentation tasks Saad et al. (2010), where the advantages of an uncertainty-ware approach become clear. Therefore, the presented workflow utilizes an uncertainty-ware segmentation approach to help medical users in estimating the risks of planned corridor for a keyhole surgery.

Azimian et al. Azimian et al. (2013) presented a visual system to perform preoperative planning of surgeries that helps determining proper surgery robot configurations. This is a suitable method to create an awareness of uncertainty in the planning process. Unfortunately, this methodology does not indicate which tissues are affected through the surgery. In contrast to this, the presented methodology offers a visualization that indicates the affected tissue of a patient while considering the underlying uncertainty information.

Razmi et al Razmi et al. (2015) presented a planning tool for surgery corridors that include uncertainty information. The resulting visualization gives medical users a good overview about the risks of a surgery. Unfortunately, the approach, does not allow users to try different surgery corridor configurations and compare them. Therefore, the presented system forms a workflow that assists medical doctors in planning a keyhole surgery and communicates the image uncertainty throughout this procedure.

3. Application Analysis and Requirements

A keyhole surgery is a minimally invasive surgery technique, that helps minimizing the trauma of healthy tissue or organs Raveenthiran (2010). Therefore, medical doctors utilize a thin corridor to access the target structure of a surgery. In order to achieve a successful surgery outcome, this corridor needs to be planned carefully. Therefore, medical doctors utilize image data, such as CT scans or MRT scans and try to identify possible and proper surgery corridors. In clinical daily routine, this can require a large amount of time, as the standard reviewing method of medical image data is not able to assist properly in the determination of a surgery corridor. The state of the art slice-by-slice reviewing method is not able to give an spatial impression of the surgery corridors and the affected tissues. Furthermore, it does not allow the comparison of surgery options and discussion of risks. Therefore, this work aims to provide a workflow that allows medical doctors to plan surgery corridors based on image data. To achieve this, the following requirements need to be fulfilled.

R1: Determination of Proper Surgery Corridor Geometries *Shamir et al. (2012).* The geometry of a surgery corridor is the key point leading to a successful surgery outcome. A correct position, that interferes minimally or not at all with important structures of the human body as well as a proper diameter that allows the proceeding of the surgery needs to be determined during the planning procedure.

R2: Communication of Risks *Shamir et al. (2012).* In many scenarios surgery paths need to be located very close to important human tissues or an intersection with the tissue cannot be avoided completely. Therefore, medical doctors need to be aware of this scenarios to be able to react to complications during the surgery itself. A workflow for keyhole surgery planning needs to include and communicate this type of information to be useful for medical doctors.

R3: Comparison of Options *Trope et al. (2015)* . While planning a keyhole surgery, medical doctors try to determine the best option of all possible surgery corridors, therefore a system in assisting in keyhole surgery planning needs to be able to test different diameters of surgery corridors and different geometries. For those corridors, medical doctors need to be capable of inspecting the affected tissues and especially review areas that cannot be determined clearly due to uncertainty contained of the underlying image data.

R4: Fast and Easy to Use *Gillmann et al. (2016).* In order to promote a novel workflow in clinical daily routine, the workflow needs to address the user group, their needs and their manner of decision making. In clinical daily routine, planning of surgeries needs to be accomplished fast and reliable to be suitable for a daily use. Therefore, the goal of a novel visual workflow is to provide a keyhole surgery analysis tool that is easy to use, with an proper computational amount. In addition medical users need to be able to use the tool without having deeper knowledge of computational concepts.

R5: Inclusion of Uncertainty Information *Gillmann et al. (2016).* As medical image data is affected by uncertainty due to the image reconstruction process, this uncertainty needs to be communicated to create an awareness of unknown situations during the surgery process. Therefore, the goal is to know the position of the desired structure that needs to be reached in the keyhole surgery and its positional uncertainty. Furthermore, surgery corridors, that are crossing areas that cannot be determined clearly need to be indicated or highlighted. This information is very important thus medical doctors are aware, that the path is crossing an area that could not have been determined based on the underlying image data.

4. Methods

According to the defined requirements in Section 3, this work aims to present an uncertainty-aware workflow for keyhole surgery planning using hierarchical image semantics. The general workflow can be reviewed in Figure 1. Starting with the input image data I and its' uncertainty quantification, users can define an hierarchical image semantic, which is a fuzzy image segmentation resulting in user-defined hierarchical segments. Next, medical doctors can define arbitrary surgery paths that they want to examine. In a third step, our workflow provides an intuitive linked view, that presents a surface view of the queried surgery corridors and a 2D view containing the segments, that are affected by the surgery corridor. In the last step, users can select surgery paths that fulfill specific requirements. The following sections will explain each step in detail.

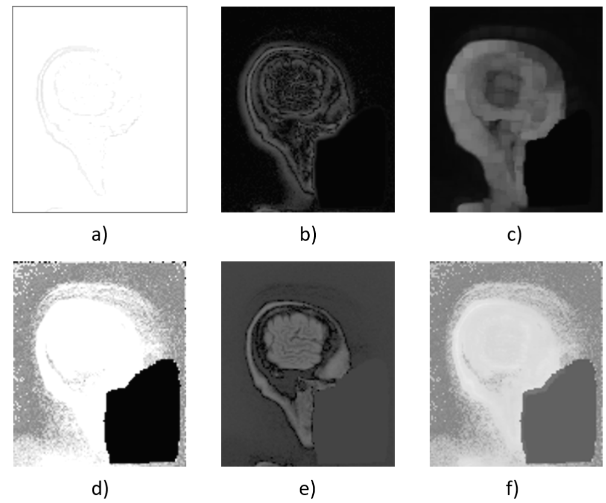

Fig. 2. Uncertainty quantification of image data. Error measures as a) acutance, b) gaussian error, c) local contrast, d) local range and e) salt and pepper error define a high-dimensional error vector. The length of this error vector (f) is the resulting uncertainty of the input image.

4.1. Uncertainty Quantification

The basic principle of the presented approach is the communication of the input image uncertainty throughout the entire keyhole surgery planning procedure. To achieve this, a proper uncertainty quantification of the input image I is required. In this paper we utilize the image uncertainty quantification presented by Gillmann et al. Gillmann et al. (2017). The approach uses a set of error measures, that are able to estimate the error of each pixel and create an high-dimensional error vector. This is important, as different error measures focus on different mathematical aspects. The length of this error vector of a pixel results can be used as an uncertainty indicator for the respective pixel as the vector is long, when multiple error measure have a high output, whereas the error vector is short, we the underlying error measures have a low output.

Figure 2 shows the error outputs for a slice of the brain tumor dataset and the resulting length of the error vector. The images show, that the error response for the single errors are varying massively. Figure 2 shows the resulting length of the error vector, which is utilized throughout the presented workflow to communicate the uncertainty of the input image.

4.2. Hierarchical Image Semantics

In order to help medical users to inspect surgery corridors, their location in the human body and especially the effected tissues, it is required to segment the input image data in order to

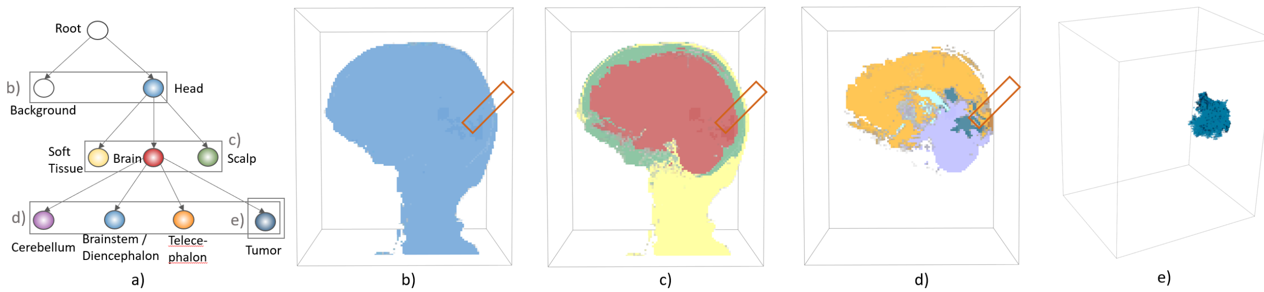

Fig. 3. Example segmentation output generated by the hierarchical image semantic approach. a) Resulting segmentation tree T capturing the objects and their subobjects selected by the user. Visualization of the segmentation result of one slice for b) the first level of the segmentation, c) the second level of segmentation of the foreground, d) the third level of segmentation of the brain including a segment of the brain tumor. The orange boxes indicate a possible surgery path to reach the tumor. e) Volume visualization of the tumor segment.

define different areas of the human body. To accomplish this, the presented workflow utilizes the concept of **hierarchical image semantics**, an fuzzy and hierarchical image segmentation approach especially designed for users from the medical area for Review (a).

The method describes an intuitive image segmentation approach, where users can define arbitrary segments and set seed points for each of the segments. Based on this definition, the utilized methodology outputs a fuzzy segmentation result. In addition to that, users are enabled to re-segment specific segments arbitrarily often. The segmentation result can be reviewed intuitively and medical doctors are enabled to adjust their input parameters until they are satisfied with the segmentation result.

The key principle is an separation of superior objects nodes into its child nodes. Therefore, the algorithm assumes, that the root segmentation node (the entire image) owns all pixels completely. Throughout the segmentation process, this ownership is separated to the child nodes of the tree according to the defined segments of the user.

The method outputs an segmentation tree capturing, the users understanding of visible objects in an image and their substructures $T(I)$. Each node $n \in T$ captures an image as well, containing the ownership, that a specific voxel belongs to the selected segment. This image is referred to as O_n. In addition, each segmentation node obtains an user-defined color C_n, that can be used for visual indication of which voxels belong to a specific node and how strong this ownership is. The method is especially designed for medical applications. All segments can be designed to map the natural understanding of the organs and tissues, that a medical user has for the input image. As organs, contain of suborgans and substructures, their structure can be mapped directly in the segmentation result.

To improve the uncertainty communication throughout this process, we modified the ownership of the root segmentation node to express pixels, that are affected by uncertainty utilizing the length of the error vector as shown in Section 4.1. If the ownership for a voxel to the root segmentation node is 0, this means, that the underlying image voxel is highly affected by uncertainty and should not be considered in the segmentation process. On the other hand, if the ownership of a voxel is 1, the voxel is trustworthy and can be utilized completely in the segmentation process. This is an important adjustment of the segmentation algorithm to ensure, that the image uncertainty is propagated along the computational pipeline of the presented method.

Figure 3 shows a possible output of a hierarchical image semantic applied to the MRI dataset capturing a human head. The brain of the patient contains a tumor, that needs to be identified. Figure 3 a) shows the resulting segmentation tree and its contained segment. The input image is segmented into foreground and background considering the uncertainty quantification of the underlying input image data (a). The foreground is further segmented into bones, soft tissue and brain (b). The brain can be further segmented into its compartments and the contained tumor. Figure 3 d) shows a volume rendering of all the image data containing the ownership of the tumor class. The voxels are visualized by the color assigned to the tumor class and the ownership stored in the respective node. Using this type of visualization users can review their segmentation output and adjust the input parameters until they are satisfied. Figure 3 b-e) indicates a potential surgery path. The two-dimensional representation is not able to indicate the entire spatial information required to judge the quality of the selected surgery path. Contrary to this, a three-dimensional representation would lead to visual clutter. Furthermore, the surgery path needs to be reviewed in all three levels of the hierarchy to identify the tissues, that are affected by the surgery path. This motivates a novel visualization approach to help medical doctors to understand which human tissues are affected, as shown in the following.

4.3. Definition of Surgery Paths

In order to investigate the quality of a surgery corridor, users can define an arbitrary amount of different corridors, that they are interested in investigate further. Therefore, the geometry of an surgery corridor needs to be defined. As usual in clinical daily routine, keyhole surgeries are assisted by medical devices, that help implementing the surgery corridor. Based on the mechanics of such an device, starting points of a surgery corridor are located on the surface of a sphere. The center of the sphere is the endpoint of the surgery corridor, which needs to be located at the target of the surgery.

To define the geometry of a surgery corridor c, we assume an cylindrical shape. To define a cylinder, we require a line segment l and an radius r. As users can define an arbitrary amount

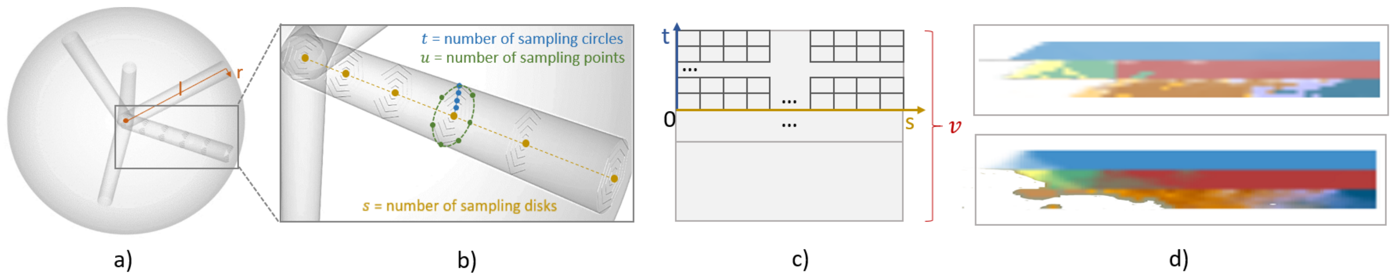

Fig. 4. Surgery path definition, sampling and visualization. a) Sampling sphere and with 5 random surgery paths. b) Sampling of a single sampling path through sampling spheres. c) Components of the resulting visualization images according to the sampling parameters. Example surgery path visualization using d) Maximum Sampling and e) Average Sampling. f) Hierarchical Image Semantic utilized for the sampling process.

of such corridors, all start points of these corridors need to be located on an user defined sphere m, represented by a position p_m in space and a radius r_m. The presented system assists users in defining the circle as well as placing the required settings for surgery paths. Based on the geometry definition, users can query, visualize and refine the surgery arbitrary corridors.

Figure 4 a) shows a user defined sphere m. Based on the sphere, 5 surgery corridors are defined. All surgery corridors origin on the surface of the sphere m and end in the center of the sphere. Resulting from this their length is always r_m. We allow users to set arbitrary points on the sphere surface to define surgery corridors.

4.4. Visualization of Surgery Paths

In order to allow users to compare surgery corridors, we provide an interactive multi-view system, consisting of two visualization types. First, the visualization consists of a volume view showing the queried tunnels. The volume view shows a surface representation of the human body, the target structure and its uncertainty and the queried path geometries. Second, the system provides a 2D view showing the sampled surgery tunnels and the tissues, that are affected considering the user defined hierarchical image semantic. The visualization techniques required for these views will be discussed below.

4.4.1. Sampled View

As medical doctors are interested in the tissues and structures of the human body that are affected by a surgery path, we provide a sampling view, that visually encodes the tissues of the human body that are affected by each surgery path.

To accomplish this, the presented view needs to visualize all queried surgery corridors and the entirety of all affected structures depending on the underlying segmentation information. Therefore, a three-dimensional visualization is not suitable, as the utilized segmentation is hierarchical and the visualization of one level in the hierarchy would result in visual clutter.

To solve this problem we adopt the principle of curved planar reformation Mistelbauer et al. (2013), where sampling planes are utilized to flat each disk in a volumetric structure. In the presented case, the surgery corridor needs to be sampled thus it can be shown as an image. Therefore, the user sets parameters to define the sampling of each surgery corridor are utilized to sample and visualize to create an intuitive visualization.

The sampling is a spherical sampling around the center line of each cylinder. Users can define the amount of sampling disks (s) along the centerline and the number of sampling circles (t) located at the sampling disks with their number of sampling points (u). An example of this sampling can be found in Figure 4 b). Depending on the set parameters, the algorithm produces an image with the size of $s \times (v * t)$, where each pixel captures an accumulation of a samplings disk output (reffig:sampling c)). For the accumulation different strategies can be utilized. In this paper, we present the two common ones *maximum sampling* and *average sampling* Kanitsar et al. (2002). As the underlying hierarchical image segmentation needs to be sampled, we need to adjust the principles to be suitable for our input.

In addition, the hierarchical structure of the segmentation tree needs to be expressed in the resulting visualization. Therefore, each visualization can be separated into different subimages, each representing one layer of the segmentation tree. Therefore, users can inspect the sampled output of each layer and therefore understand how the surgery corridor affects structures and its substructures.

Usually, a maximum intensity sampling searches for the maximum value probed along the sampling sphere and uses this value for visual representation. In the presented case, this is not possible directly, as the segmentation does not provide one image. Instead, depending on the considered nodes in the segmentation tree, multiple images need to be utilized to produce a visualization. Resulting from this, a maximum intensity sampling tries to find the node outputting, the maximum total weight on a sampling sphere. For the resulting visualization, the node outputting the highest total weight determines the color of the pixel visible in the resulting image.

To include the uncertainty information of the segmentation result in the sampling view, we adjust the opacity of the out image. Therefore, we set the opacity to the maximum of (1-n) of all segmentation nodes that are sampled. As Gillmann et al. **?** mentioned in their paper, this expresses the uncertainty of the segmentation result as shown in Figure 4 d).

Contrary to this, an average sampling allows to average the sampled colored weighted by the sampled total weight of each node. The user can select the utilized sampling technique, required to show an image of the surgery corridor as shown in Figure 4 d). Contrary to the maximum sampling, the opacity of the average does not need to be adjusted. In cases, where tissues cannot be determined clearly, the visualization shows a

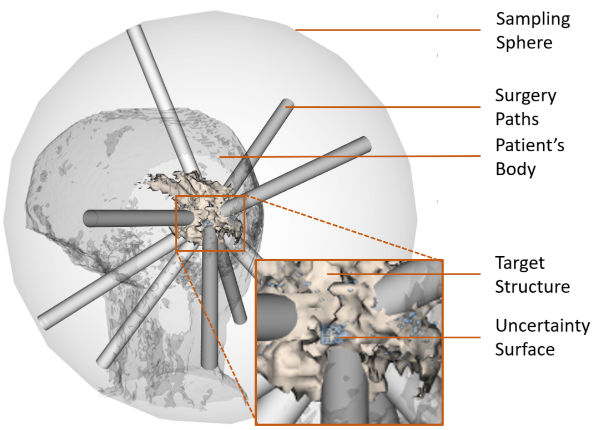

Fig. 5. Geometry visualization of the presented methodology. The visualization captures the outer surface of the human body (grey), the target structure (light orange) and its uncertainty surface, as well the user defined surgery paths.

mixed color of those two tissues.

4.4.2. Surface View

The surface view combines geometric surfaces representing the most important aspects of the surgery. An example is shown in Figure 5. It consists of three main visualizations: a surface representation of the human body, a surface-representation of the queried surgery corridors and an uncertainty-aware surface representation of the target structure.

The surface for the visualization of the surgery corridors can be directly created from the corridors geometry definition. The surface of the human body can be generated by depicting the node in the segmentation tree, that represents the human body. We utilize a marching cubes algorithm to extract the representing surface based on the probability volume for the respective node. Users can depict the iso-value required for the marching cubes algorithm.

Different from the previous objects of the surface view, the visualization of the target structure will be shown as an uncertainty-aware geometry. The size, shape and location of the target structure is an important indicator that determines a proper selection of the surgery corridor geometry as the size of the target structure directly corresponds with a proper surgery corridor radius. As the exact size of the target structure is hard to determine due to the uncertainty of the input image, the surface view aims to visually encode the resulting positional uncertainty of the target structures geometry. Therefore, we use an uncertainty-aware surface visualization presented by Gillmann et al. for Review (b). The approach models the positional uncertainty of the target structure by introducing a surrounding surface covering all possible geometries with an user-defined probability. Therefore, users have a visual tool to estimate the size, shape and position of the target geometry and are enabled to adjust the size of the surgery corridor.

4.5. Querying of Surgery Paths

In order to determine the quality of a surgery path, the presented workflow allows users to query defined surgery corridors. This is accomplished by an evaluation of each surgery corridor. Each node in the segmentation tree can be rated with an importance i by the user. In addition, the surgery corridor needs to be sampled to determine which structures are affected by the surgery corridor to generate the sampling view. We utilize the same sampling spheres and their output for the ownership for each node to create a rating function that combines the user assigned importance values with the sampled values.

The entirety of all sampling points is referred to as S. For each sampling point, all probability volumes of the segmentation tree can be sampled as $s(I_n)$ with $s \in S$ and $n \in N$. A rating function $r(c)$ for a surgery corridor can be computed by combining all probabilities for the entire segmentation tree to a weighted sum, defined as:

$$r(c) = \sum_{n \in N} \sum_{s \in S} I_n(s) * (1 - i(n)) \tag{1}$$

The function outputs a real value between [0, inf]. The closer the value is to 0, the less proper is the defined surgery corridor according to the user defined rating of the segmentation nodes. In other words, the corridor would harm a large amount of human tissues that where declared as undesired by the users. Contrary to this, a high value of $r(c)$ means, that the corridor path is located in human structures, that can be affected by the surgery corridor.

Based on the rating function $r(c)$, the user can define a ratio that expresses the amount of surgery corridors that can be inspected further. Therefore, medical user can select an percentage that works as a threshold. If the user defines a threshold of 0%, it means, that solely the best rated surgery corridor will be displayed. Contrary to that, if the user selects a percentage of 100%, all sampled paths are visible.

The rating function $r(c)$ gives medical doctors an suitable impression of which surgery corridors are suitable and helps users identifying settings for proper surgery paths directly. When querying surgery paths, the respective geometry visualization of a path is either fully visible or very transparent.

5. Results

In the following section the presented workflow is used to plan keyhole surgeries of different purposes. The presented approach was implemented using C++ with the vtk Schroeder et al. (2006), itkMolkentin (2007) and Qt Johnson et al. (2013) libraries. The following section will present two keyhole surgery planning scenarios performed by the presented workflow.

5.1. Example 1: Tumor Removal Surgery

A prominent example for keyhole surgeries is the removal of a brain tumor. The planning of this type of surgery is an crucial factor for its success. While the tumor needs to be removed completely, a second goal is to keep the damage to the human brain minimal.

Figure 6 shows the application of the presented approach to a real world dataset from the cancer imaging archive Scarpace

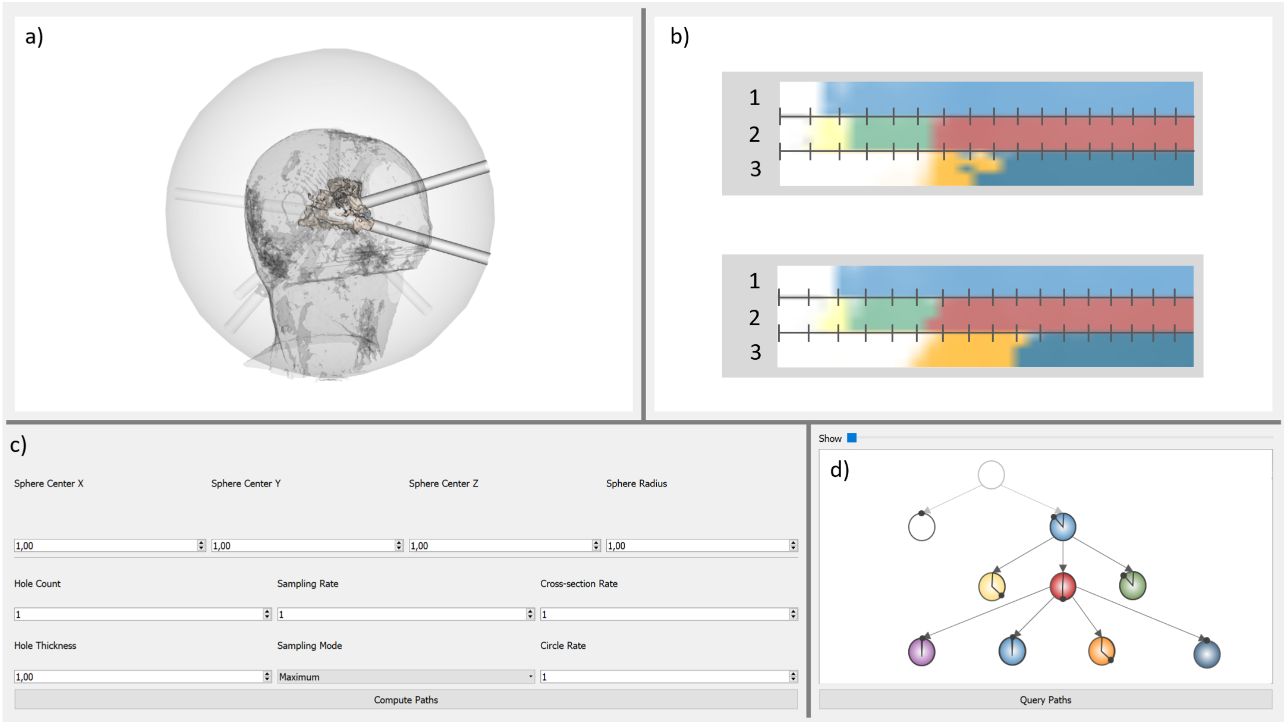

Fig. 6. Uncertainty-aware surgery planning applied to a brain tumor removal scenario. a) Geometry visualization. b) The best two surgery paths according to the user defines importance values for each node. c) GUI interface to define surgery paths and the sampling sphere. d) Hierarchical image semantics with the user defined importance values for each node.

et al. (2016). The example shows a brain dataset that contains a tumor Clark et al. (2013) with the size of 256x215x200.

Figure 6 a) shows the surface representation of the sampling sphere and the surface of the patients head. In addition, the surface of the tumor is shown inside the head surface with its uncertainty surface. The center of the sampling sphere is positioned inside the tumor (Figure 6). 20 surgery paths where generated and evaluated by the user. Figure 6 b) shows the two best suitable path according to the rating function. The importance of the cerebellum was set to 100% to indicate, that this structure is not allowed to be affected by the surgery path. These setting can be made through the interface shown in d). They are designed as pie charts, that are empty, when the structure is not important and full, when the structure is extremely important. The sampling strategy is set to maximum sampling.

The first level visualization of the surgery corridor shows how the surgery paths moves through the background of the image (white) until it reaches the patients head (blue). For the human head, the underlying intersected structures are the cranial bone (green), the soft tissue (yellow) and the finally the brain (red) of the patient.

Reviewing the intersected tissues on the third level of the hierarchical image semantic, it can be shown, that the surgery corridor, solely interferes with the cerebrum and the brain of the the patient. As defined in the importance function, this structure can be interfered. Figure 6 b) shows the two best options for these settings. In the geometry view they are indicates as opaque. The linked view systems fuses two important aspects of the surgery scenario: the spatial location of the surgery corridor (geometry visualization) and the affected tissues in all level of hierarchies of the hierarchical image semantic (sampling view).

The result shows, that the presented system can be used to find the best surgery corridor out of the defined surgery corridors, by utilizing the defined rating function. The interface is structured clearly and the visualizations are linked to form an intuitive representation.

5.2. Example 2: Kneecap surgery

A further example for the application of the presented approach is the planning of a kneecap surgery. The dataset shows a CT scan of the lower body of a patient. Both legs are captured.

The target of the surgery corridor lies behind the left knee cap, as the medical doctors aims to reconstruct the tendon of the patient. As a first step, the input image data is segmented using the concept of hierarchical image semantics. The resulting segmentation tree can be reviewed in Figure 7 a). The resulting segmentation tree captures the left food and re-segments it into its soft tissue and the entirety of all bones. Based on this segmentation, the bones are re-segmented into the single bones of the human leg , as shown in Figure 7 m).

The geometry visualization is generated, as shown in Figure 7 a) and b). It contains, the left foot of the patient as the surrounding structure, the uncertainty-aware geometry visualization of the knee cap and 10 surgery paths, that should be tested for their quality to lead behind the knee cap while not injuring the knee cap or any other bone of the patient.

The goal for a usable surgery path was to not interfere with the kneecap of the patient. Therefore, the importance values of the knee cap is set to 0% which means, that it should not be

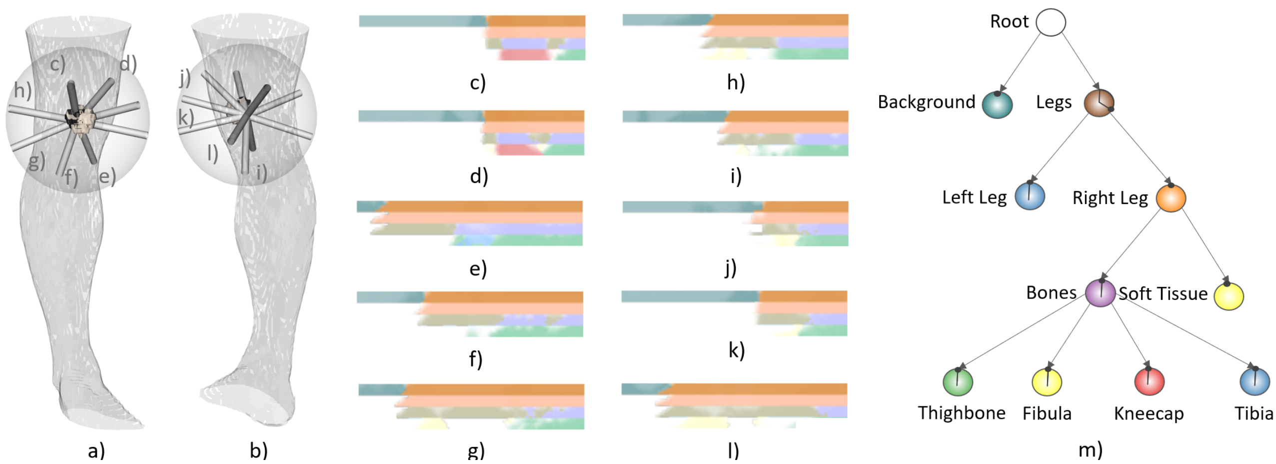

Fig. 7. Uncertainty-aware keyhole surgery planning applied to a kneecap surgery scenario. a) Geometry visualization front view. b) Geometry visualization back view. c-l) Surgery paths sorted by the user defined importance values (from bad to good). m) Hierarchical image semantic with the user defined importance values.

affected at all. As the right foot is not targeted in the surgery, its probability is also set to 0%. The same holds, for the remaining bones in the human body. Differently to that, the soft tissue of the left foot is supposed to be affected by the surgery path and therefore set to 100%.

The resulting rating of the ten different paths is shown in Figure 7 c) -l). They are sorted from bad to good. c) and d) insult the knee cap of the patient and are therefore rated as worst. Followed by that, the algorithm outputs all paths, that are affecting the lower bone of the patient. This is not desired too. The last path (l) holds the only path, that does not intersect with any bone of the patient and is therefore rated as the path suitable path.

The example shows, that the querying function helps users select surgery paths according to the importance for each node not to be interfered by the surgery path. The visual system allows users to further inspect the queried paths and review which tissue are affected and at which position on the surgery path.

6. Discussion

The presented workflow was designed to fulfill the defined requirements for keyhole surgery analysis mentioned in Section 3. The following section discusses how these requirements are tackled.

In order to assist medical doctors in determining proper surgery corridors ($R1$) the presented system allows to review the surgery corridor in two different manners: first, as a geometric representation showing users if the target structure can be captured by the selected surgery corridor. Second, the presented system allows a visual representation of the hierarchical image semantic, that are affected by the selected surgery corridor.

To communicate possible risks of a surgery ($R2$), the presented workflow is capable of representing different surgery paths and rate their quality according to user defined ratio determining the importance to not affect a specific tissue.

The presented system helps medical doctors in comparing different options of surgery corridors ($R3$). This is accomplished by representing the affected tissues as a 2D view, that can be reviewed easily. In addition, the rate function $r(c)$ is able to query surgery corridors according to the users setting on how important it is to avoid specific tissues.

In order to provide a fast and easy to use workflow that assists in planning keyhole surgeries ($R4$), the presented workflow guides the user through the steps of surgery planning carefully implementing suitable visual analysis methodologies. By using different visualizations and interactively connect them, medical doctors can use the presented workflow without the need of a deeper knowledge of computer science principles.

At last, the communication of uncertainty ($R5$) is accomplished by quantifying the uncertainty of the underlying image data, propagate the uncertainty information along the single steps of the workflow and finally visually communicate the information in all visualizations. Firstly we started with an uncertainty quantification of the input image, which is utilized to improve the uncertainty propagation of the hierarchical image semantics. Although hierarchical image semantics are an uncertainty-aware concept itself, the image uncertainty quantification improves the resulting segmentation results as it determines areas which are more reliable then others. To communicate uncertainty in the surgery path definition process, we allow the definition of arbitrary surgery paths, show how they intersect with the hierarchical image semantic and its contained uncertainty as well as allow an querying to find paths that fulfill specific requirements. In addition to that, the geometry view holds an uncertainty-aware visualization of the target structures geometry to communicate possible sizes and locations to the user.

We presented the designed workflow to our collaborators that work in clinical daily routine and they gave us an very positive feedback. Some statements are listed below:

- I like the idea that I can test different surgery paths and see which tissues are affected

- I like the presented visualization and interaction method as I can directly select tissues that should not be affected
- I think this method can tackle a large variety of clinical applications such as biopsy, vascular surgery and brain tumor removal scenario
- This is a method that people are willing to pay money for as it changes a surgery from try and error to a specific plan that is not to be optimal

7. Conclusion and Future Work

This work presents an uncertainty-aware workflow for keyhole surgery planning that is based on hierarchical image semantics. To achieve this, we analyzed the needs of medical doctors for planning a keyhole surgery analysis. The resulting workflow combines suitbale visualization and analysis methods to offer an interactive methodology for defining an hierarchical and fuzzy image segmentation, allow users to test multiple surgery corridors, query them to find proper suitable surgery corridor settings and visually inspect the results. The presented approach is general, thus it can be used for arbitrary settings of keyhole surgeries. By the design of our workflow we achieve an easy to use methodology that can determine proper surgery paths, communicate risks during the surgery, allow comparison of surgery options and communicate uncertainty information.

As a future goal, we aim to accomplish a clinical study with the presented system to identify improvements for the presented workflow. In addition, an inclusion of possible surgery robot geometries is planned.

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